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Sikorska, Anna E ; Viviroli, Daniel ; Seibert, Jan

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Abstract

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1 Introduction

Hydrological floods are caused by largely varying processes and, thus, classification of flood events into flood types and the determination of their respective frequency is important for a better understanding and prediction of floods. While flood frequency analysis provides information on the periodical occurrence of floods and their magnitudes, it does not provide the reasons for the flood occurrence [*Merz and Blöschl* , **2008**]. Yet, the effects of flooding on the inundated area will alter depending on the specific flood behavior, i.e., the distribution of the flood volume over time, which can be attributed to a flood type. Hence, the classification of floods at the event level, given along with the information on their frequency, may support flood risk management at monitoring, assessment and decision-making stages.

The classification concept relies on clustering objects into a manageable amount of homogeneous groups on the basis of their similarities or relationships [*Platts* , **1980**]. Generalizing properties of group classes make it possible to further transfer classes into other independent objects. Hence, classification schemes have become well established in different research fields. Examples include chemistry (periodic table), biology (taxonomy), medicine (viruses), physics (character of flow), pedology (soil groups), or meteorology (clouds).

In terms of hydrological studies, classification schemes have been developed to cluster rivers [*Rosgen* , **1994**], hydrological regimes [*Haines et al* ., **1988** ; *Robinson and Sivapalan* , **1997** ; *Zhang et al* ., **2012**], hydrographs [*Hannah et al* ., **2000**], ecological river state [*Biggs et al* ., **1990** ; *Snelder et al* ., **2005**], catchments [*Wagener et al* ., **2007** ; *Sawicz et al* ., **2011** ; *Sivakumar et al* ., **2015**], and to some extent floods [*Merz and Blöschl* , **2003** ; *Diezig and Weingartner* , **2007**]. The basic foundation of flood classifications is that meeting similar hydrological or catchment conditions will result in a similar hydrological response [*Sivakumar and Singh* , **2012**]. Thus, exploring flood causes allows for delineating flood-type patterns and to improve relationships between these patterns and salient flood characteristics, which can then be transferred on. In this way, it is possible to predict a hydrological response for other events or at different locations [*Carrillo et al* ., **2011**]. Such classification schemes find practical applications in estimating flow behaviors in regions with limited observed data [*Castellarin et al* ., **2001** ; *Carrillo et al* ., **2011**], in regionalization of hydrological model parameters [*Hundecha et al* ., **2008**] or in supporting flood frequency analysis [*Acreman and Sinclair* , **1986** ; *Sauquet and Catalogne* , **2011**]. Yet, due to the tremendous variability of hydrological processes, a generic scheme for classifying floods is missing so far.

One possible way to cluster floods is to identify some measures of similarity such as hydrological, meteorological, or geological attributes using multivariate or principal component analysis [e.g., *Nathan* *and McMahon* , 1990 ; *Hall and Minns* , 1999 ; *Harris et al* ., 2000 ; *Laaha and Blöschl* , 2006 ; *Isik and Singh* , 2008 ; *Sawicz et al* ., 2011 ; *Ali et al* ., 2012]. The reader is referred to *Sivakumar et al* . [2015] for a more detailed review on this topic. *McDonnell and Woods* [2004] and *Oudin et al* . [2010] argued that observed physical similarity does not necessarily lead to a similar hydrological behavior and suggested to emphasize process-oriented criteria in classifying hydrological behaviors. Some attempts in this direction have already been taken by *Merz and Blöschl* [2003] and *Diezig and Weingartner* [2007], who classified events by their flood genesis.

Another group of techniques rely on data-driven artificial neural networks (ANNs) also known as self-organizing maps (SOM) [e.g., *Thirumalaiah and Deo* , 1998 ; *Di Prinzio et al* ., 2011 ; *Ley et al* ., 2011 ; *Kumar et al* ., 2013]. This approach uses similarity of input patterns in high-dimensional space in order to single out homogeneous groups in low-dimensional space. As a measure of the similarity, different catchment attributes are usually applied.

As an interesting alternative, regression or decision tree algorithms have been proposed [e.g., *Rao and Srinivas* , 2006 ; *Diezig and Weingartner* , 2007 ; *Sauquet and Catalogne* , 2011 ; *Galelli and Castelletti* , 2013 ; *Tehrany et al* ., 2013], in which the classification is based on successive binary splittings of a given data set into smaller subgroups according to decision attributes until finally obtaining groups of similar flood events. The decision attributes are defined according to some established similarity measures. Traditionally, these attributes have been defined as sharp thresholds, i.e., either one class or another is assigned.

Although such a decision tree, called crisp tree [*Solomatine and Dulal* , 2003 ; *Sauquet and Catalogne* , 2011], leads to clearly attributed classifications, it has severe drawbacks for flood classification. First, a crisp approach assumes that certain conditions will lead inevitably to a certain flood behavior (flood type). However, as recent studies have shown, flood processes demonstrate natural variability and stochasticity [*Han et al* ., 2002 ; *Sikorska et al* ., 2015] and are usually induced by mixed causative mechanisms [*Waylen and Woo* , 1982 ; *Merz and Blöschl* , 2003], which makes it difficult to categorize them in a classical, unambiguous way. Second, due to the enormous variability of flood processes and the existence of uncertainty in real-world problems, class boundaries represented as sharp thresholds may not be defined clearly [*Parajka et al* ., 2005 ; *Qin and Lawry* , 2005]. Yet, a small shift in a threshold value may result in assigning a different class. Thus, in the context of flood prediction, a reliable measure of uncertainty in predicted variable is of vital interest [*Sikorska et al* ., 2012].

Given the above, it becomes clear that a flood classification which represents overlapping flood classes and accounts for uncertainty in flood identification would be more justified. Therefore, within this work, we propose a process-based framework for classifying flood types according to flood patterns with the help of a fuzzy decision tree scheme. Fuzzy trees have already been successfully applied in different fields for classification and prediction of landslides [*Pradhan* , 2013], water quality [*Schärer et al* ., 2006], or river flow [*Han et al* ., 2002]. A fuzzy tree, in contrast to a crisp tree, represents class attributes as soft thresholds and thus enables overlapping classes to be represented. We further represent these thresholds in an innovative way as a probability measure with a degree of their acceptance. By means of the fuzzy tree, we can also acknowledge the uncertainty present in the identification of flood processes and inherent in observed data, and thus we are able to provide more reliable class estimates than before. Next, we use the frequency of different flood-type occurrence to classify catchments according to their observed flood patterns, which we call a catchment flood signature. Classifying catchments by their flood type is particularly useful in assisting with planning flood management strategies at a catchment scale. The novel aspect of this work is the flood-type classification in a fuzzy approach. This allows for "in between" classifications. We also demonstrate that this approach is less sensitive to uncertainties in the classification attributes than the classical crisp approach. This paper presents a proof-of-concept on the proposed flood classification, which is tested with a small sample of nine catchments in Switzerland.

2 Study Area and Methods

2.1 Study Catchments

We developed our approach based on a sample of nine selected Swiss mountainous catchments of different properties and flood regimes without significant human alteration of runoff (Figure 1). Within this sample, seven catchments have independent flow data and two of them are nested. Six of these catchments are situated above 1000 m. a.s.l. and one above 2000 m. a.s.l. (see Table 1 for details). For these catchments, detailed information was available including catchment geology, topography, land use, glacier cover, as well as 30 year long-term data sets, i.e., 1981–2012, which consist of hourly areal and daily gridded meteorological observations (precipitation and temperature), and streamflow measurements at the catchment outlets at both time resolutions.

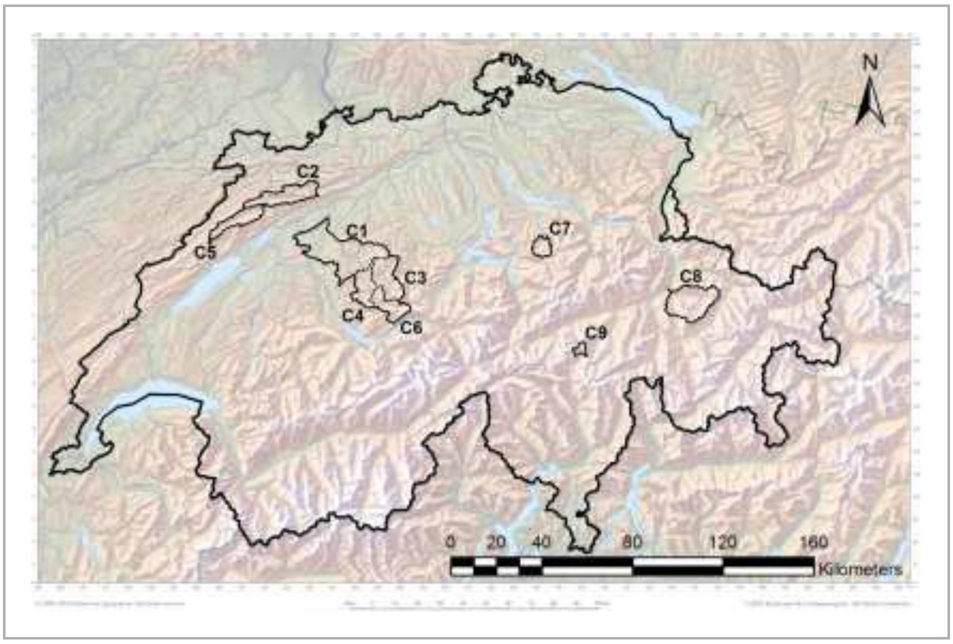

Figure 1.

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Location of the nine study catchments in Switzerland.

Table 1. Properties of the Study Catchments Sorted by the Increasing Average Elevation

ID	River	Gauging Site	Elevation[a] (m. a.s.l.)	Area (km^2)	Glacier (%)	Regime Type[b]	No. of Events[c]
C1	Emme	Wiler	841	939	0	ps	279
C2	Birse	Moutier	907	183	0	n-pj	259
C3	Ilfis	Langnau	1002	188	0	n-ppa	189
C4	Emme	Emmenmatt	1004	443	0	n-ppa	152
C5	Suze	Sonceboz	1076	150	0	n-pj	207
C6	Emme	Eggiwil	1249	124	0	n-ppa	278
C7	Minster	Euthal	1318	59	0	ndt	292
C8	Plessur	Chur	1917	263	0	na	168
C9	Somvixer Rhein	Somvix	2421	22	6.7	b-g-n	178

a Mean elevation of the catchment.

b River regime type according to *Weingartner and Aschwanden* [1992]; ps—pluvial supérieur; n-pj—nivo-pluvial jurassien; n-ppa—nivo-pluvial préalpin; ndt—nival de transition; na—nival alpin; b-g-n—b-glacio-nival.

c Number of events per analyzed period of 30 observation years separated according to the method presented in section 2.3.

2.2 Classification of Flood Types

In natural catchments, floods are generally induced either by extreme rainfall, rapid snowmelt (or glacier-melt), or rainfall on snow events [*Merz and Blöschl* , 2003-2005, 2009 ; *Diezig and Weingartner* , 2007]. To identify these types, usually a classification focused either on meteorological (climatological) or catchment conditions is used. Within the first group, floods have been classified into tropical, convective, and frontal types [*Hirschboeck et al* ., 2000], snow-related or rainfall-related floods [*Gupta and Dawdy* , 1995 ; *Renard and Lang* , 2007], or according to their seasonality [*Bayliss and Jones* , 1993] or seasonality and flood indicators [*Piock-Ellena et al* ., 2000]. Another group of authors focused instead on catchment conditions. Thus, floods were classified into rainfall, snowmelt, or glacier melt events using either antecedent precipitation [*Waylen and Woo* , 1982], snow water equivalent [*Sui and Koehler* , 2001], runoff components [*Loukas et al* ., 2000], or catchment area [*Blöschl and Sivapalan* , 1997 ; *Robinson and Sivapalan* , 1997]. The drawbacks of these approaches is that focusing only either on meteorological or catchment conditions does not allow the distinction between different events. Thus, in another approach, *Merz and Blöschl* [2003] merged both catchment and meteorological conditions to classify events in the Austrian Alps into flash, short-rainfall, long-rainfall, rain-on-snow, and snowmelt floods, while *Gaál et al* . [2014] merged these types into snow-related, synoptic, and flash floods. Such a process-oriented flood typology is convenient because it accommodates most processes governing natural hydrological floods. Yet, for the Swiss Alps (and other high-altitude mountainous catchments with glaciers), it is useful to consider another flood type. Indeed, floods driven by glacier ablation pose severe problems in the Swiss Alps every year [*Huggel et al* ., **2004**]. The dissimilarity in the dynamics between the glacier and the snow meltwater in terms of the peak seasonality and the melted water equivalent means that the glacier-related floods should be treated separately from the snowmelt floods. Following these considerations, *Diezig and Weingartner* [**2007**] adapted the classification of *Merz and Blöschl* [**2003**] to the Swiss Alps by explicitly accounting for glacier melt floods.

In the present work, we further adapt the classification of *Diezig and Weingartner* [**2007**] and thus specify six main flood types, which are the most relevant ones in mountainous catchments including high altitude glaciated areas. These are:

1. Flash floods (FF) induced by short intensive rainfall usually lasting less than half a day and locally exceeding the infiltration capacity, occurring mostly in the storm season and of a local range (limited to a small catchment or a subcatchment);
2. Short-rainfall floods (SRF) occurring due to short rainfall with maximal duration of one day and a high-intensity rapidly exceeding the infiltration capacity, usually of a larger local range than FF and possible during the whole year;
3. Long-rainfall floods (LRF) driven by long lasting rainfall of several days or weeks and usually of low-intensity which gradually fills the storage capacity, usually of a regional range covering nested catchments, possible the whole year;
4. Rain-on snow floods (RoSF) occurring due to rainfall on existing snow cover, which initiates melting, possible during the whole year but conditioned on the availability of the snow cover in the catchment;
5. Snowmelt floods (SMF) caused by melting of snow cover initiated by a rapid increase in air temperature with insignificant rainfall, possible during the whole year but with a different peak seasonality depending on the catchment altitude, i.e., in lowlands they occur mainly at the end of winter or beginning of spring, while in the mountains they mainly occur in spring and summer due to delayed melting of snowpack; and
6. Glacier-melt floods (GMF) caused by glacier melting due to increase in air temperature with insignificant rainfall, possible only in (partly) glaciated catchments, the seasonal peak is usually shifted towards summer, with respect to SMF, due to higher solar radiation required to initiate melting of glacier ice located at higher altitudes (and lower air temperatures).

2.3 Flood Event Separation

Identification of a flood-type requires that observational data are partitioned into events. To also deal with nonrainfall induced flood types (section 2.2), in this work we used a method that combines a peak overthreshold (POT) modeling concept [*Lang et al* ., **1999**] with a response timing concept [*Rinderer et al* ., **2015**]. This method is independent from precipitation information and relies only on flow dynamics. Hereby, the flow series are first filtered to locate the local maximums defined as these points in the flow series which show a significant inflection between the rising and the falling limb of the hydrograph observed over several time intervals. Maximums, which are higher than a certain threshold flow and which occur after a certain threshold period from the proceeding maximum, are defined as flood peaks. Similarly, the local minimum is defined for each peak flow as the point with a significant inflection between falling and rising flows observed over several time intervals. The local minimum directly proceeding the peak is defined as the starting point of an event. The end of the recession curve is set at the first point on the falling limb of hydrograph at which observed flow falls below 20% of the event peak value, following *Rinderer et al* . [**2015**] and which, in our case, was also found as a suitable value for nine catchments. Next, we define a flood event as the period between the event starting point and the end of the recession flow curve. Next, the base flow is linearly interpolated between these points and the direct flow is extracted from the total flow over the entire observation period. Note that this approach allows multiple peak events to be considered when flows between two successive peaks do not fall below 20% of the first peak value. This method has three parameters which, for hourly streamflow data, are the peak threshold (mm h^{-1}), the time elapsed between two successive events (h), and the minimum duration of the event (h). A new event is then defined if all of the following conditions are met: (a) direct flow occurs, (b) peak flow is higher than a peak threshold (here average yearly flow), (c) time elapsed after the last event is higher than an assumed threshold (here 1 day), and (d) the event duration is longer than an assumed threshold (here 1 day). In this way, we ensure independence of events, required in flood frequency analysis [*Stedinger* , **2000** ; *Kundzewicz and Robson* , **2004**]. Using this method has an advantage in that it ensures that all major flood events are selected, over the analyzed data series. Additionally, separated events can be further accepted or rejected depending on the magnitude of their peak flow or on the number of maximal peaks desired per year. By limiting the number of maximal peaks per year to the largest one, the method becomes similar to the annual maxima series approach. Alternatively, different methods as graphical separation or digital recursive filtering techniques could be also applied [e.g., *Tallaksen* , **1995** ; *Arnold and Allen* , **1999** ; *Eckhardt* , **2008**].

2.4 Flood Indices

The occurrence of a certain flood type (section 2.2) is controlled by the interaction of static and dynamic indices. Dynamic indices vary for the same catchment over different flood events but are expected to be stable for a certain flood type. These indices include such factors as meteorological conditions (e.g., duration and amount of precipitation), timing of occurrence, or current favorable hydrogeological conditions (catchment wetness, snow cover). Conversely, static indices are expected to be constant over a span of time (and events) for the catchment given that its conditions remain unchanged. Among others, these include catchment geology, topography, climate, area, land-use, and a glacier ratio. We lump all dynamic and static indices into flood indices.

2.5 Definition of Flood and Catchment Flood Signature

The behavior of a flood is governed by specific catchment and antecedent event conditions. Thus, this behavior can be attributed to flood indices. It is, however, unlikely to identify flood type based on an individual index because this may be identical for different types [*Merz and Blöschl* , **2003**]. Yet, a composition of indices is more likely to be flood type-specific, which makes it possible to identify flood type and predict its behavior. In this paper, we call such a unique composition of flood indices a *flood signature* . In a similar fashion, some flood types are more likely to occur in a certain catchment and glacier melting floods may exclusively occur in glaciated catchments. We call such a flood preference in a certain catchment a *catchment flood signature* . The catchment flood signature can be identified either from flood indices using regionalization methods without observed data (not covered by this paper) or by means of frequency analysis of assigned flood types in the catchment using past observations (presented in this paper). While the first method allows for qualitative analysis of flood types that could occur in the catchment, the frequency method gives the possibility to represent the likelihood of flood type reoccurrence in a quantitative way given long-term observed data.

2.6 Flood-Type Signatures

For each of the six defined flood types (section 2.2), we specified a unique flood signature based on flood indices. We limited the selection of indices to those which were previously tested in flood typological [*Merz and Blöschl* , **2003**] and regionalization studies [*Viviroli et al* ., **2009**] and tested them with nine selected catchments (section 2.1). To also keep the approach applicable to ungauged catchments, we selected only salient indices which potentially can be specified from precipitation and catchment information only (often available for a catchment) without explicitly considering observed runoff data. However, for a proof of concept, we implicitly use runoff data to compute snow-related indices (see section 2.7). For ungauged catchments, these indices need to be regionalized (see further discussion in section 4). We further excluded all static indices that are unspecific for flood types in natural conditions. As a result, we selected eight essential indices with seven dynamic and one static index. For these indices and for different flood types, we established characteristic values (thresholds) from the literature and previous studies [*Grebner* , **1990** ; *Geiger et al* ., **1991** ; *Wüthrich* , **1999** ; *Viviroli et al* ., **2009**], which define flood signatures (Table 2). These signatures were then used as reference for identifying flood types of analyzed events.

Table 2. Flood-Type Signatures, Their Attributes, and Threshold Values

ID	Flood Index	Unit	Flood Type and Attributes					
			FF	SRF	LRF	RoSF	SMF	GMF
Td	Timing[a]	(day)	0501–0930	0101–1231	0101–1231	1001–0331	0101–1231	0501–0930
	Precipitation:							
P	Amount[b]	(mm)	≥12	≥12	≥12	≥12	<12	<12
D	Duration	(days)	≤0.5	[0.5;1]	≥1	≥1		
I	Intensity[c]	(mm/h)	≥7.6					
GC	Glacier cover[d, e]	(%)	<5	<5	<5	<5	<5	>5
SC	Snow cover[d, e]	(%)	<5	<5	<5	>5	>5	
SM	Snowmelt[e]	(mm)	<1	<1	<1	≥1	≥1	≥1

CW	Catchment Wetness[e, f]	(%)	≥90	<90

a A day of the year is expressed in a MMDD format, where 0101 refers to the 1 January and 1231 to the 31 December.

b According to *Geiger et al* . [**1991**], *Diezig and Weingartner* [**2007**], and *Wüthrich* [**1999**].

c According to *Grebner* [**1990**].

d Assumed as a static index, expressed as a percentage of the catchment area.

e Index computed from the hydrological model HBV, see section 2.7.

f Specific for the study catchment, represented as percentage of the average maximum value.

2.7 Computation of Flood Indices

Assigning a flood type to an event requires computation of the selected flood indices (Table 2) for each separated flood event in study catchments. To extract information on precipitation characteristics (duration, amount, intensity) and event timing, we used observed hourly areal precipitation data available from MeteoSwiss. The glacier area ratio was estimated from catchment characteristics, while time variant estimates of snow cover, snow melting, and catchment wetness were derived for each flood event with the conceptual hydrological model HBV [*Bergström* , **1995** ; *Lindström et al* ., **1997** ; *Seibert* , **1999**] with the version HBV-light [*Seibert and Vis* , **2012**]. To provide estimates on these indices aggregated over events, the HBV model was calibrated for nine catchments using 30 year long-time series of daily gridded precipitation and streamflow, using the proportion of $\frac{2}{3}$ data for calibration and $\frac{1}{3}$ for validation. The model parameters were optimized by means of a multiobjective approach using Nash-Sutcliffe, volumetric error, and efficiency for logarithm discharge as objective functions of the same weights. To consider parameter uncertainty, 100 calibration trials were performed and using this set of 100 optimized parameter sets the above state variables were quantified by averaging 100 simulated state variables. The average Nash-Sutcliffe efficiency achieved for the nine catchments was equal to 0.72, the efficiency for logarithm discharge was 0.74, and the relative volumetric error to 4% for the validation period.

2.8 Decision Tree for Flood-Type and Catchment Identification

2.8.1 Flood Tree Concept

To identify the type of flood event, each analyzed event needs to be screened for its similarity to the flood signatures defined in Table 2. To this end, we developed a flood decision tree which relies on a query scheme, similar to *Diezig and Weingartner* [**2007**]. The tree input consists of a vector with flood indices computed for the event as specified in section 2.6. The proposed tree is built up of branches, nodes (queries), and ends up in leaves. Each leaf represents one of the six flood types (see Figure 2). The evaluation of the tree is executed by examination of sequential queries which correspond to flood indices, called attributes here. Each query is allowed to occur only once along the branch and is defined in a binary way with only two possible branches to be taken. A query represents a test on an attribute, whereas each branch represents an outcome of the test. For each attribute, a threshold value T_H is specified according to flood signatures and Table 2. The specified T_H splits the space of possible outcomes into two subgroups. This threshold value is next compared with the corresponding flood index in the input vector computed for the event and the outcome of this test determines to which subgroup the input value will be assigned. With each successive query, the space of possible outcomes is reduced till only one outcome remains (leaf), which represents the identified flood type.

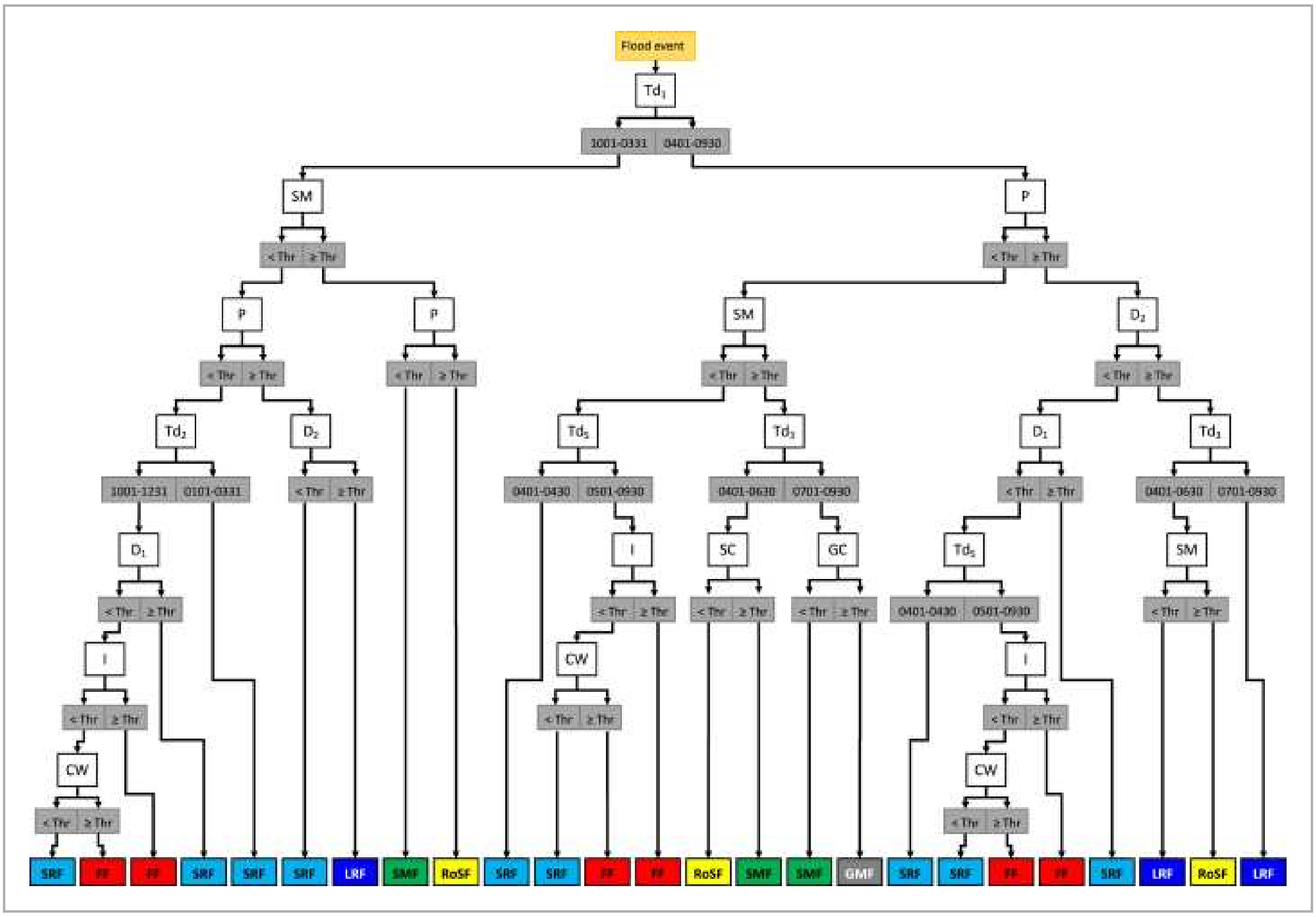

Figure 2.

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Decision tree for flood-type identification. Notation: FF—Flash Flood, SRF—Short Rainfall Flood, LRF—Long Rainfall Flood, RoSF—Rainfall on Snow Flood, SMF—Snow Melt Flood and GMF—Glacier Melt Flood. Flood indices: Td—timing (Td_1, Td_2, Td_3, and Td_s split the year into winter/summer, autumn/winter, spring/summer, or storm seasons), SM—snowmelt, P—precipitation amount (mm), D—precipitation duration (h) (D_1 and D_2 separate short and long-lasting rainfall events), I—precipitation intensity (mm/h), CW—antecedent catchment wetness (%), SC—antecedent snow cover (%), and GC—glacier cover (%).

2.8.2 Crisp Decision Tree

For comparison, we first used a crisp decision tree, i.e., we assumed that it is possible to assign only one dominant flood type for each event. Thus, it may be seen as a deterministic approach, in which meeting certain conditions leads evidently to assigning a certain flood type. We represent tree attributes as sharp thresholds similarly to a crisp tree scheme [*Solomatine and Dulal* , **2003** ; *Sauquet and Catalogne* , **2011**]. This means that if the input value exceeds or is equal to the threshold value (T_H), the corresponding branch is taken with *the degree of acceptance equals 1* and the second branch is rejected or vice versa. In this way, two branches starting from the same node are mutually exclusive and it is not possible to take both branches at the same time. If at any node the test on the attribute results in input data falling out of the defined threshold, i.e., the degree of acceptance equals 0, the whole branch is terminated at the current depth. As a result of the tree evaluation, one obtains only one flood type per event which represents a dominant flood type. Consequently, mixed flood types are not allowed.

2.8.3 From Crisp Toward Fuzzy Approach

The main drawback of the classical crisp tree is that due to its sharp thresholds it is very sensitive to noise, which may come from imprecise observed input data, imprecisely estimated threshold values, or inherent errors of the method itself [*Qin and Lawry* , **2005**]. Another problem is that due to the existence of uncertainty in parameterization of hydrological processes [*Sikorska et al* ., **2015**], threshold values may not be defined accurately. These imprecisions will be reflected in tree attributes and their thresholds, and may become critical for clustering inputs lying close to the threshold values. For these values, only a small change in the defined threshold may result in a different grouping of the input data and consequently in assigning a different flood type. Finally, due to randomness present in flood processes, it may not be possible to uniquely identify a flood event based on selected flood indices. To overcome these problems, we adopt a fuzzy approach [*Rao and Srinivas* , **2006**] which allows us to incorporate all these uncertainties into the flood classification.

2.8.4 Fuzzy Decision Tree

As a modification of the classical crisp tree (section 2.8.2), we assumed that there is some unavoidable vagueness in the classification as different processes may simultaneously contribute to the flood formation. Thus, one event can be governed by mixed flood types. However, instead of using a descriptive combination of mixed types, we chose to use a quantitative description of the six main types by assigning degree of membership to the different flood types. Degrees of membership represent the flood type likelihood, i.e., the likelihood that the event can represent a certain type of flood. To allow the assignment of mixed flood types, we represent tree attributes this time as soft thresholds in a similar way to the fuzzy concept [*Pradhan* , **2013**]. These are defined as a threshold value (T_H) with a certain range assigned ($T_H \pm X$), which can be seen as the uncertainty in attributing the threshold value. For the indices of seasonality, we assume the threshold X is equal to 5 days, while for the quantitative indices equal to the value of 20% of the threshold. Next, for each computed flood index in the input vector at each attribute test, we assign a corresponding degree of acceptance that an event belongs to a certain flood type computed in the following way. For the input value equal to the T_H , we assign the degree of acceptance equal to 0.5, which means that the event can be represented by the flood type indicated by T_H with the likelihood of 0.5. Then, for all input values falling into the threshold interval, i.e., from $T_H - X$ to $T_H + X$, we attribute the degree of acceptance between 0 and 1 assuming a linear interpolation. These boundary values correspond to the lower and upper threshold range, respectively. Consequently, for values falling below and above the threshold interval, we assign the value of 0 or 1 (Figure 3). In this way, each of the branches is evaluated till the leaf. The overall degree of acceptance for each of the flood types is computed as the product of all degree values assigned at nodes along the branches and the sum of values from all leaves. The values at each query (node) and at leaves always sum up to 1.

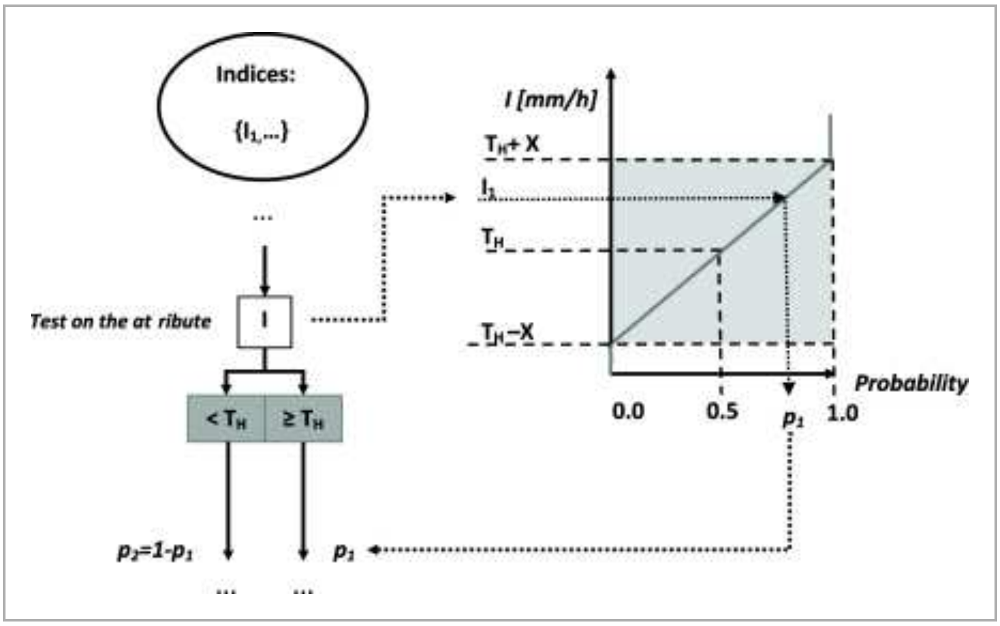

Figure 3.

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Probabilistic description of soft thresholds (gray rectangles) and assigning the degree of the acceptance for inputs in the fuzzy decision tree. T_H represents the threshold for the tree attribute, X determines interval borders for the soft threshold, p represents the probability measure or the degree of the acceptance, and I is precipitation intensity (mm/h).

As a result, one obtains a spectrum of all flood types with assigned degrees of their belonging to each flood type. The dominant flood type is the one with the highest value allocated. If a certain type is not allowed to occur under given conditions (based on queries), its degree of acceptance is set to 0. In a similar fashion, if only one type can possibly occur, it receives the value of 1.

2.8.5 Tree's Application to Catchment Classification

The proposed flood tree (section 2.8.1) can be applied to identify individual events (*flood classification*) by determining either a dominant process (crisp tree) or a spectrum of significant processes (fuzzy tree) that have led to the observed flood. No less important, analyzing long-term flood patterns over numerous past flood events helps to identify dominant flood types in the catchment and thus allows a catchment to be classified according to its likelihood of flood-type occurrence (*catchment classification*). Such information is useful to better describe flood processes in catchments and thus can support the design of flood management strategies (see further discussion in section 4).

2.9 Tree Performance: Robustness Test

A classification cannot be validated against observations since flood event types cannot be directly measured and are always based on some classification. However, it is possible to evaluate the approach by taking into account flood history or by carrying out a sensitivity analysis of the tree outcomes. For this, we performed a Monte Carlo experiment, in which we assessed the robustness of the tree classification with respect to changes in assigned threshold values T_H for each index and each flood type. Thus, we represented the tree attributes (threshold values) as random variables instead of formerly assigned values T_H, for which we define a probability density function (i.e., pdf(T_H)). As a simple approach, we use a truncated normal distribution bounded below to zero and with a mean equal to the formerly elicited attribute value T_H and a standard deviation of 25% of this value. The normal distribution reflects our belief in the fair choice of the attributes. From these pdfs, we next randomly sampled a single value for each attribute, which was assigned as a new attribute value T_H''. This new T_H'' value was then used to redefine sharp and soft thresholds in the crisp and in the fuzzy decision tree. Particularly, for the crisp tree, this T_H'' was used directly as a new threshold value while in the fuzzy tree the new redefined intervals were established as $T_H''\pm x$. The attribute sampling was repeated 10,000 times for each tree while all attributes were sampled simultaneously.

3 Results

3.1 Statistics of Analyzed Flood Events

In over 30 years of available observations in the nine study catchments, we identified between 150 and 280 flood events per catchment (see Figure 4). Flood events were observed during the whole year with the highest frequency in the spring-summer season. Most of those events were long-lasting (of several days), with a precipitation amount between 10 and 100 mm per event, moderate intensity (1–10 mm/h), and with a low snow cover at the event beginning (<5%) in most catchments. Exceptions were catchments C8 and C9 with a median ratio of the snow cover of 90% and 70%, respectively. The latter was also the only partly glaciated catchment with a glacier cover ratio of 6.7% of the total area. Apart from these two catchments, snow-melt was rather insignificant (<1 mm), while catchment antecedent conditions were rather wet for most of the analyzed events.

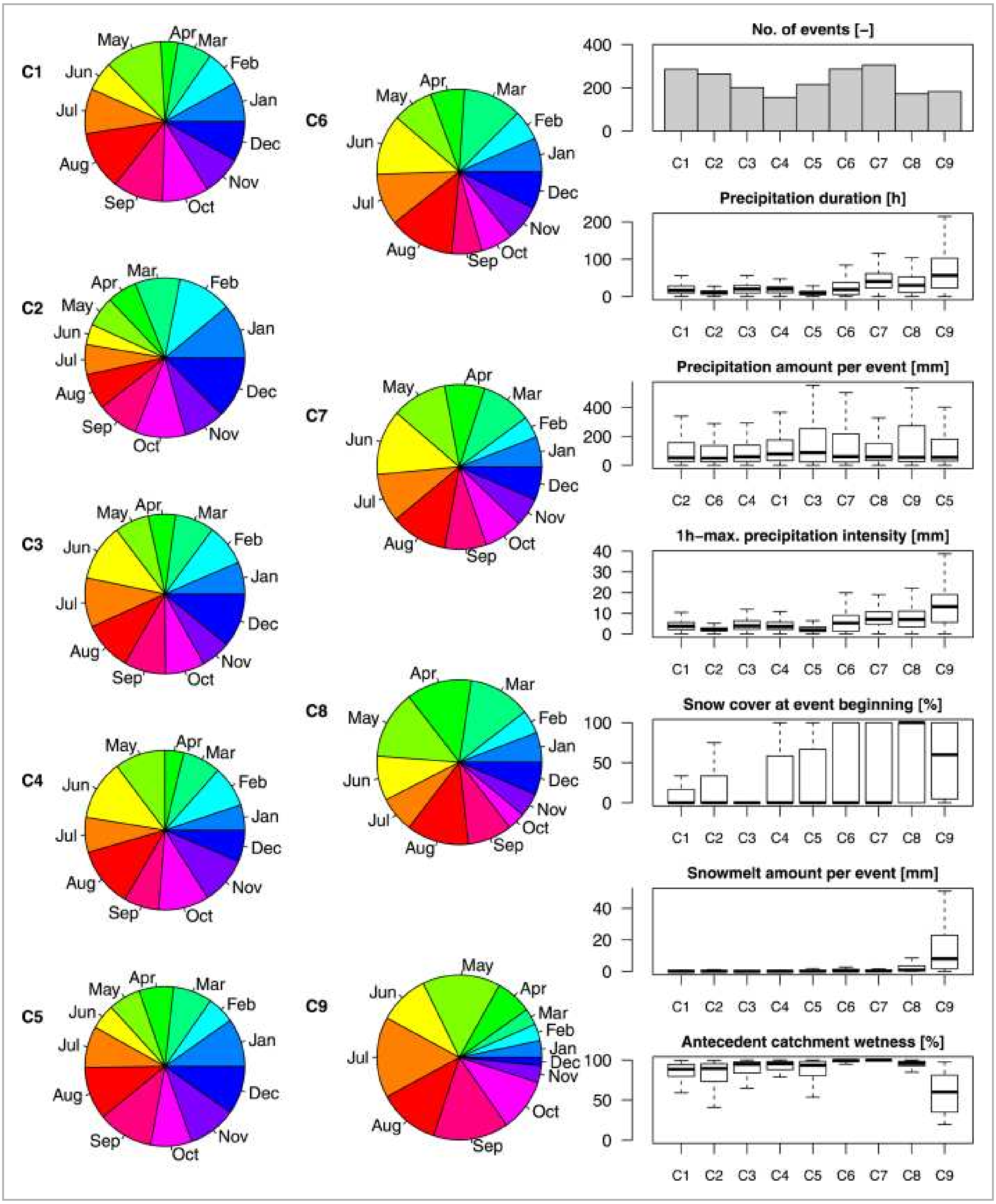

Figure 4.

Open in figure viewer

Summary of flood indices for the nine (C1–C9) study catchments. Pie plots present event seasonality, box-plots summarize characteristics of analyzed flood events over 30 years of observations.

3.2 Event Classification

As it follows from the method assumptions, in the crisp decision tree each event was identified as one flood type, whereas in the fuzzy decision tree most events were classified as a spectrum of different probable types, which corresponds to the degree of acceptance for each identified type. Not surprisingly, the resulting event classification was different in both approaches for most of the events (compare Figures 5 and 6). In the fuzzy approach, the type with the highest degree of acceptance assigned is the one which mostly contributed to flood generation. This type would correspond to the expected (one) flood type identified with the crisp approach. Although this is not always necessarily the case, in 91% of all analyzed events in nine catchments the unique flood type identified with the crisp tree agreed with the flood type receiving the highest degree of acceptance (but lower than 1!) in the fuzzy approach.

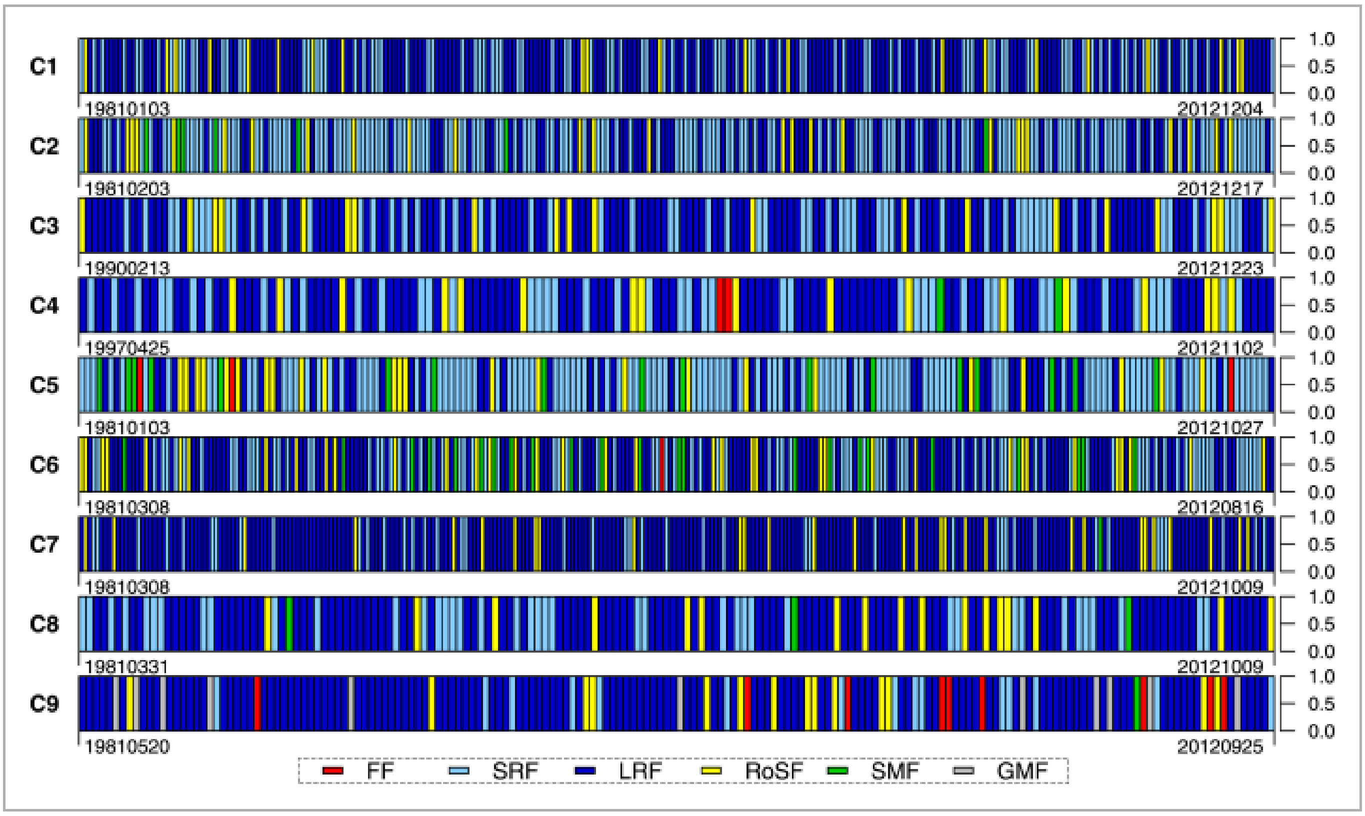

Figure 5.

Open in figure viewer

Event classification with the crisp decision tree in the nine study catchments. Each box corresponds to one event without considering its duration. X-axes represent flood events in the chronological order, while y-axes the degree of the type event acceptance. As can be seen, each event is classified as a single flood type.

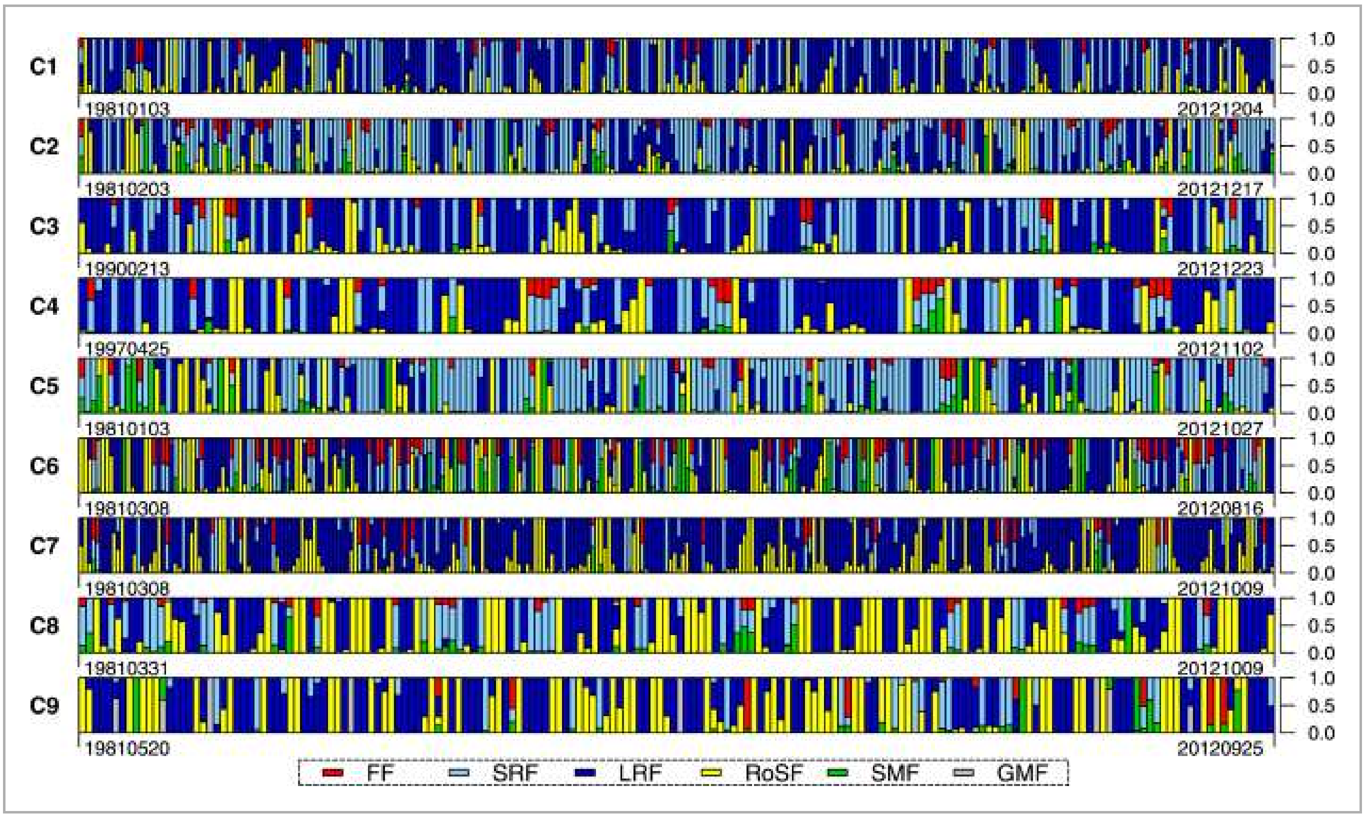

Figure 6.

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Event classification with the fuzzy decision tree in the nine study catchments. Each box corresponds to one event without considering its duration. X-axes represent flood events in the chronological order, y-axes the degree of the type event acceptance. As can be seen, most events are classified as a mixed flood type, which nicely pinpoints the difference in event classification when using both approaches (compare with the Figure 5).

3.3 Catchment Classification

Similarly, analyzing flood patterns over all identified events led to different classification of the study catchments depending on which tree was applied. In the crisp approach, flood processes in all catchments were classified with mainly three types. These were short rainfall floods (SRF), long rainfall floods (LRF), and rainfall on snow floods (RoSF). Other flood types were only sporadically identified. When using the fuzzy approach instead, the catchments were described by all flood types with the highest values (degrees of acceptance) given to three types: short rainfall floods (SRF), long rainfall floods (LRF), and rainfall on snow floods (RoSF). Thus, the resulting catchment flood signature, computed as the frequency of flood-type occurrence aggregated over all observed events, was different in the crisp and in the fuzzy approach (Figure 7).

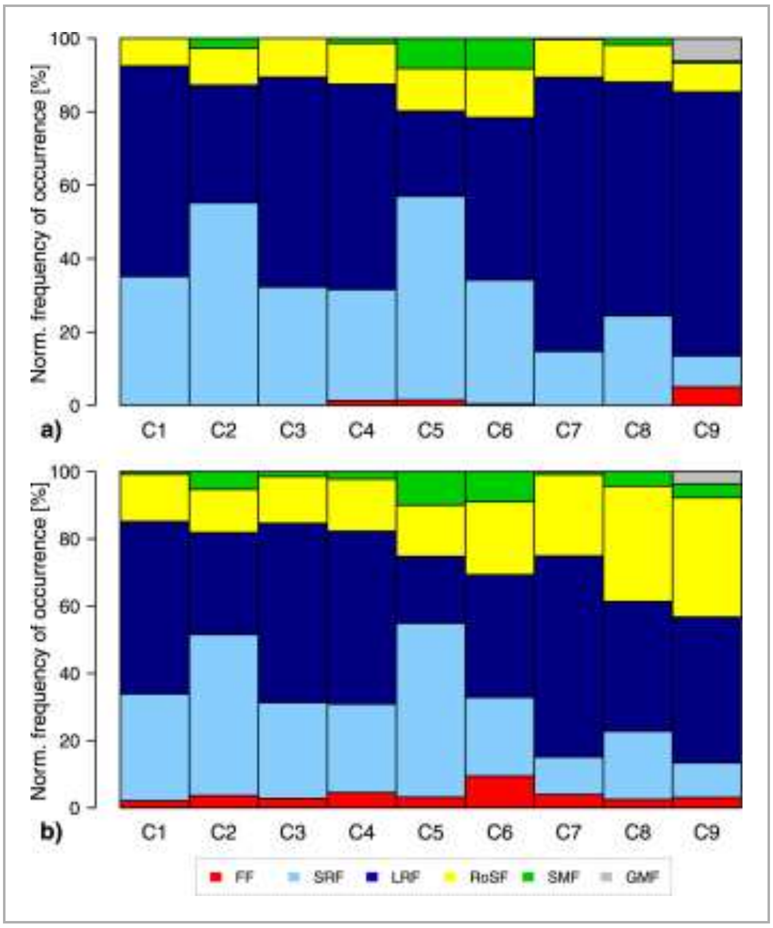

Figure 7.

Open in figure viewer

Differences in study catchment (C1–C9) classification with the crisp (a) and the fuzzy (b) decision tree. The *x*-axes correspond to the normalized frequency of flood-type occurrence estimated from long-term analysis over all analyzed events in the catchments.

3.4 Tree Robustness

As expected, the Monte Carlo experiment showed that the crisp tree is more sensitive to changes in assigned threshold values than the fuzzy tree because medians over all simulations and all events resulted in alternating the catchment flood signature for all catchments identified from observed flood events (compare Figures 7 and 8). Interestingly, in some catchments flood types, which were never identified with the crisp tree, were assigned when using the same tree but with threshold values altered during the Monte Carlo simulation. In contrast, the catchment flood signatures identified with the fuzzy tree were preserved over the Monte Carlo simulations in most cases. Moreover, the results from the crisp tree aggregated over all MC simulations became similar to those of the fuzzy tree in most catchments (compare violin plots in Figure 8).

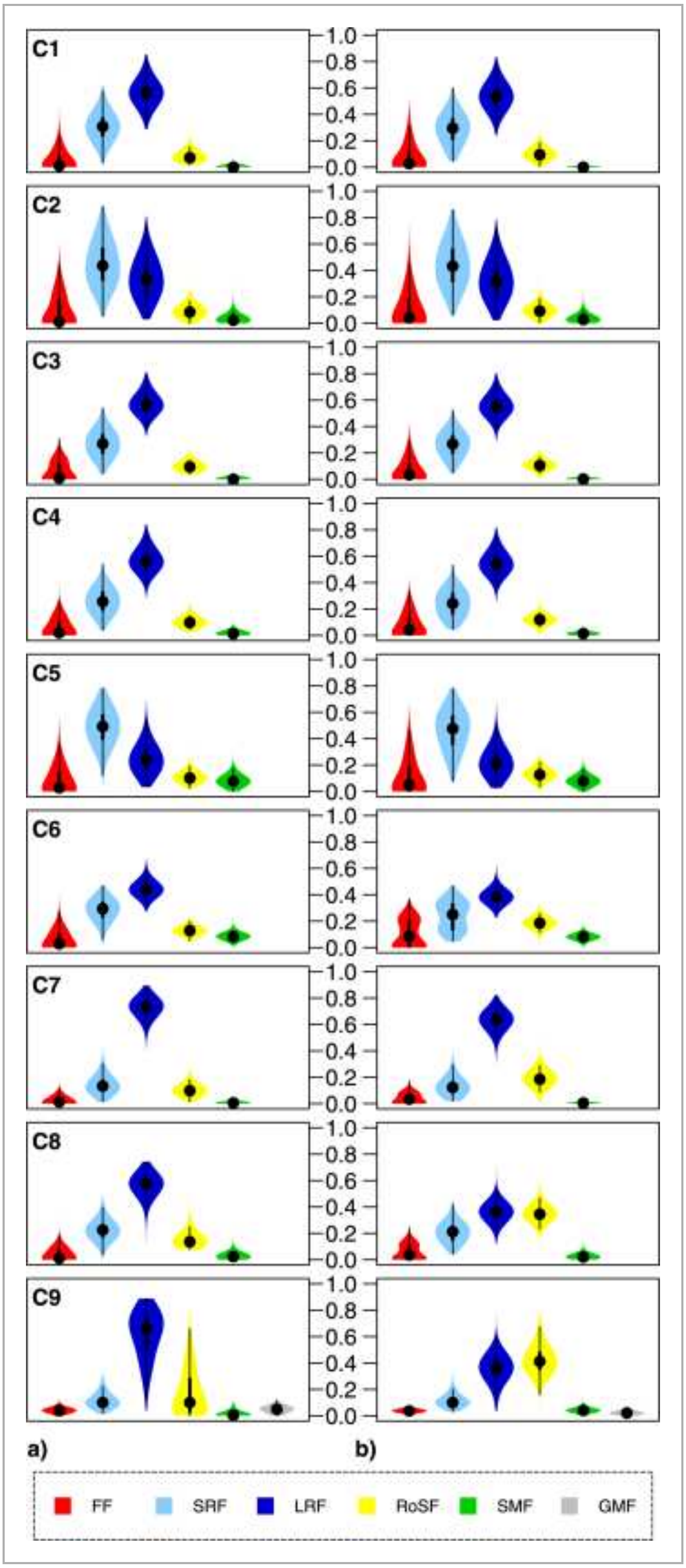
C1
C2
C3
C4
C5
C6
C7
C8
C9
1.0
0.8
0.6
0.4
0.2
0.0
a)
b)
FF
SRF
LRF
RoSF
SMF
GMF

Figure 8.

Open in figure viewer

Monte Carlo robustness test of catchment classification with the crisp (a) and the fuzzy (b) decision tree over all events in the nine study catchments. The violin plots indicate the degree of acceptance for each flood type over 10,000 MC simulations and averaged over all analyzed events. The black dots stand for the median value. Two things can be noted by comparison with the Figure 7. First, flood types, not identified before in the crisp tree, are now assigned. Second, the Monte Carlo simulation results of the crisp tree become similar to those of the fuzzy tree in most catchments.

4 Discussion

4.1 Test Case Results

According to the tree outputs, the catchments studied were classified as dominated by three main processes, i.e., short rainfall, long rainfall, and rainfall on snow floods. This finding is in agreement with the event statistics which indicated that most of the analyzed events were long-lasting with a moderate amount of precipitation and a small or insignificant snow-melt. Yet, both the event and the catchment classification alternated depending on which approach—crisp or fuzzy—was used. This was rather expected because the focus of the crisp tree is to identify only the major process according to the screening queries, while other contributions are ignored. Thus, it is possible to identify only a *one flood type per an observed event* . In the fuzzy approach, by contrast, many types are permitted at once and, thus, we are able to also identify other minor processes affecting flood generation. Consequently, although with both approaches we usually identified the same flood type as a dominant process for most events, with the fuzzy approach most events were classified as mixed flood types. Thereby, a resulting likelihood of possible flood types and a catchment flood classification differed between both approaches in all catchments. This difference was nicely shown by the variation in catchment classification when using the fuzzy approach and by the limited number of classes assigned when using the crisp tree instead (section 3.3).

For the catchment flood signatures, we also observed that the contribution of snow-related floods increased with the catchment altitude when using the fuzzy approach (Figure 7). This seems logical as the snow cover and the snow cover duration are known to increase with altitude. This trend, however, was not observed when using the crisp approach instead because most catchments were represented by rainfall-related flood types. This finding would suggest that, in our case, snow-related floods were most often accompanied by rainfall. Because these two processes could not be isolated, the crisp classification resulted in assigning only the major process, i.e., a rainfall-related flood, while a snow contribution was omitted. With the fuzzy approach, both contributing mechanisms could be captured instead, which outperforms the use of the crisp approach.

4.2 Methodological Aspects

The proposed flood decision tree relies on a query scheme. Thus, it can capture only those processes, and their patterns, that are represented by queries. In the same manner, the resulting degree of flood-type acceptance reflects only those types that were identified with the help of queries. Therefore, this classification might alter if different queries would be asked or different threshold values for clustering events would be chosen. The use of the fuzzy tree with soft thresholds therefore ascertains that small changes in threshold values do not cause significant alteration in event nor in catchment classification (see further section 4.3). This was also proved by the robustness test (section 3.4), in which alternating the threshold values in the crisp tree led to assigning different flood classes. This effect was not observed when using the fuzzy tree. Expectedly, the results of the Monte Carlo simulations were similar for both trees, which is logical as the crisp tree with alternating thresholds becomes methodologically similar to the fuzzy tree. The advantage of the fuzzy tree is, however, a much lower computational cost because only one evaluation is needed.

Next, the queries for flood-type specification rely on defined threshold values. These values were elicited from literature and previous studies, but may have two important concerns. On the one hand, due to the existence of uncertainty and imprecise information in the real world, as well as limited knowledge on flood processes, it may be difficult to represent the thresholds as one-fold values [*Qin and Lawry* , **2005**]. On the other hand, the specified flood types, although useful, are always only arbitrary while real flood events are much more complex and may not fall into discrete classes. Therefore, the “true” values for the type differentiation do not exist.

Further, the output of the tree is represented by the spectrum of possible flood types and in the case of the crisp tree only by one type. However, the interpretation of the tree outputs is different in both approaches and therefore they cannot be quantitatively compared. In the fuzzy tree, for each flood type and each event, we assign a degree of acceptance *in the range from 0 to 1* . This value truly corresponds to the probability of occurrence inferred from the data. Thus, the flood type with the highest value assigned is the type that is the most likely to occur in the catchment. If any type is labeled with a value of 0, this flood type is unlikely to occur in the catchment (based on queries). In the crisp tree, however, flood types are attributed in a different manner. For each type, we assign the value *either equal to 0 or 1* given that only one type per event occurs and thus can receive the value of 1. The attributed value represents the degree of a type acceptance only. The type with assigned value 1 is interpreted as the major flood mechanism (based on queries). Other types are labeled with the value of 0. The assigned values, however, *do not* reflect the probability of occurrence and the type with an assigned value of 0 should be interpreted as a minor type which is *less likely* rather than *impossible* to occur. Yet, this value does not contain any information about its probability of occurrence or its contribution (degree of acceptance).

Furthermore, there are no requirements in terms of data length for event classification and the tree can even be applied to a single event. However, one flood event will usually not contain enough information to classify catchment patterns. This leads to the question of how much data (food events or years of observations) is required to capture the whole spectrum of flood causative mechanisms and to classify a catchment. Indeed too short data sets may bias the assigned catchment flood signature due to the possibility of observing random processes only which do not reflect catchment patterns. Too long series may contain biased information instead, e.g., due to the impact of changes in the catchment that are not obvious, and in terms of a very long precipitation data set also due to climate changes. In this context, 30 years of observations, used in this study, should be long enough to shed light onto catchment flood causative mechanisms. However, the analyzed data set and the catchment itself have to fulfill conditions of independence, homogeneity, and stationarity [*Kundzewicz and Robson* , **2004** ; *Stedinger* , **2000**], as it was in our case. Only then, can the resulting catchment flood signature be assumed as reliable. The shorter the data record is, the less representative the assigned catchment flood signature becomes.

Finally, the output of the tree cannot be meaningfully validated. First, because each classification is always a simplification of a complex system and, thus, classes are only arbitrary. Second, the real causative mechanisms of observed flood events are usually not known. Thus, it is only possible to judge results by looking at the flood history or by applying it to an event or a catchment of a known flood mechanism. In this respect, the available catchment characteristics not used for the flood identification can contain important information for verifying the tree outcomes. For instance, these characteristics can include the catchment mean elevation, and in our case, the catchment area.

4.3 Benefits and Limitations of the Crisp and the Fuzzy Tree

We see the main potential of the fuzzy tree in the possibility to represent a flood event as a composition of mixed causative mechanisms and to incorporate associated uncertainties into the approach. This is not feasible with the classical crisp approach.

While the possibility to represent an event as a process of mixed genesis improves the identification of flood causes, capturing compliant causative mechanisms helps to better identify the hydrological patterns of a catchment. This is important because due to randomness present in flood processes and the method itself, and uncertainty in data, it is usually not possible to uniquely classify a flood event, even moreso because in real case studies most flood events are of mixed genesis [*Waylen and Woo* , **1982** ; *Merz and Blöschl* , **2003**]. This was also shown in our case, where most events were classified as mixed-type when using the fuzzy tree.

Classifying catchments according to their likelihood of flood-type occurrence allows the behavior of future floods to be predicted in a more efficient way. Such quantitative information on flood-type likelihood is particularly useful for flood frequency analysis and should help to more efficiently plan flood management strategies at a catchment scale. While flood frequency analysis provides information only on the periodical occurrence of floods and their magnitudes (usually peak flow), it does not contain any information on the flood behavior i.e., how the flood volume is partitioned over time. In this context, the information on possible flood type is important here because floods of different geneses are expected to present a different flood volume distribution over time. Knowing how the flood volume is distributed is especially important for designing and operating reservoirs and culverts.

By representing attributes for identifying flood types as soft thresholds, the fuzzy approach offers the possibility to acknowledge the uncertainty in the choice of threshold values, in data, and in the method itself. Consequently, the tree becomes less sensitive to small changes in thresholds and its outputs are more robust, as our results showed (section 3.4). Such soft thresholds also allow for “in between” classifications of floods and catchments, which may play an important role when limited information is available for the event or the catchment. Hence, the tree becomes more suitable for ungauged regions.

The proposed flood classification is process-oriented. Particularly, it clusters events and catchments by their flood processes. Although our study was based on the analysis of a limited number of catchments (nine) and therefore presents a proof of concept, the approach itself is independent from the catchment properties. Thus, it is applicable to classify any event in any catchment according to its likelihood of a flood occurrence. In this regard, it fulfills the requirements for a generic framework [*Sivakumar et al* ., 2015]. The application to catchments of different climatic or geographical conditions should be, however, tested with a larger sample including more heterogeneous catchments.

The main limitations arise from the difficulties to validate the approach on real data sets and the need to provide long-term high-quality data for catchment classification. As discussed above, flood-type classifications cannot be validated against observed data. However, the usefulness of classifications can be evaluated in subsequent analyses of the classified events. The data requirement can be a limiting factor in some catchments but could be overcome by means of a regionalization procedure, as explained in the following section 4.4. Furthermore, although the tree itself is independent from the runoff data, these data were used indirectly to calibrate the hydrological HBV model to compute snow-related indices. The runoff data requirement may limit the application of this exact tree and modifications might be needed for catchments without such data, as discussed below.

4.4 Further Challenges in Flood Classification: Toward Regionalization

The main challenge of the tree improvement lies in its regionalization, which is a general problem of each classification. To this end, flood indices for clustering events and the information on catchment signature could be linked to catchment static properties, which could be generalized [*Burn* , 1997]. For instance, one could consider to link the tree attributes to common hydrometeorological catchment characteristics such as annual precipitation, runoff ratio, or snow-melt index. This would also make the tree completely independent from runoff data. As an alternative to calibrating a hydrological HBV model in the catchment, one could also consider using an uncalibrated HBV model with regionalized parameters instead which could be inferred from catchment characteristics only. In terms of the HBV model, such attempts have already been undertaken in the past with promising results [*Seibert* , 1999]. Obviously, using regionalized model parameters and catchment signatures brings additional uncertainty to the tree outcomes which should be considered (e.g., with the fuzzy approach). Optionally, the tree could be further extended to also include other indices. Regionalization of the tree would also allow for application to regions with limited or no observed data. Thereby, we could better identify flood processes in ungauged catchments and in this way support flood management strategies in those catchments. To regionalize the approach, however, the catchment data set should be enlarged to include more catchments with various flood governing mechanisms and also located in different climatic and geographical conditions. Adopting the tree to other conditions may require redefining the threshold values for classifying events.

5 Conclusions

In this study, we developed flood classification for identifying flood causative mechanisms at a catchment scale by means of a fuzzy decision tree. The practical value of our classification lies in the possibility to classify events and catchments according to their flood preference. We represent this preference as a likelihood measure of flood-type occurrence. Thus, a flood event is described as a spectrum of different causative mechanisms with their degrees of acceptance. Such quantitative assessment of a flood-type occurrence allows for the flood behavior to be predicted in a more efficient way. The flood tree also offers the possibility to represent its attributes as soft thresholds. This makes it feasible to formulate the uncertainty on the threshold choice and to incorporate process and method uncertainty into the approach. To demonstrate the potential of our approach, we compared it with the classical crisp approach. Based on the results from 30 year long-time series analysis in the nine Swiss mountainous catchments, we conclude that the fuzzy approach bears additional potential for analyses of flood patterns and thus provides more realistic representation of flood processes.

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